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Original Article

Convolutional Neural Network Based Data Security in Image Steganography

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Abstract *- Steganography has made significant progress in recent years but struggles with various obstacles and hurdles. Image steganography refers to the technique of maintaining privacy under a cover picture. This data might take the shape of words, pictures, or videos. This research offers a compact, simple, and fully convolutional design to incorporate a hidden picture within a cover picture and to recover the contained hidden picture from the input image. The paper bases its proposal on an in-depth learning approach and picture-based general steganography techniques. The proposed method uses Convolutional Neural Network (CNN) based steganography to hide the secret information and steganalysis to recover the secret information. Also, it focuses on performance metrics like Peak Signal Noise Ratio (PSNR), Universal Image Quality Index (UQI) and Spatial Correlation Co-efficient (SCC). The outcomes of the experiments have shown that the presented scheme has superior outcomes in terms of concealing capability, confidentiality and resilience and interpretability compared to previous deep-learning picture steganographic techniques.*

Keywords *- Steganography, Deep learning, Convolutional Neural Network, Peak Signal Noise Ratio, Universal Image Quality Index, Spatial Correlation Co-efficient.*

1. Introduction

The current decade has seen a meteoric rise in technological advancement, which has driven an explosion in the use of audiovisuals for data transmission. In most cases, the transmission is made through unsecured networks. There has been a dramatic increase in the usage of the web to transfer digital files, with users including private businesses, public entities, and even federal agencies [1]. Information security and confidentiality concerns are significant drawbacks, even though there are many benefits to using them. Although methods for concealing data have existed for some time, their relevance has been growing lately. The primary cause is the rise in social media and other online activity, leading to a dramatic spike in data sent between devices [2].

Hostile attacks, espionage, and other covert actions are more likely to occur now that many widely available technologies exist that can compromise the confidentiality and integrity of the information being communicated [3]. The most common method involves encrypting information by transforming it into an encrypted form using an embedding system [4]. One way of this kind of approach is image steganography [5]. "Stegano" and "Graphy" are the two ancient Greek terms that were combined to create the modern English term "steganography." The entire concept can be summed up as "Cover Writing." Figure 1 shows the Categorization of the Security system. Steganography safeguards the data within a cover file so the intended recipient can decode the hidden message. In contrast, an unauthorized person would be unable to do so [6]. Figure 2 indicates the Process flow diagram of the steganography used. In the steganography method, the private data is cloaked in such a manner to make it indiscernible to human vision.

Recent times have seen a surge in people's interest in artificial intelligence technology, which has emerged as an effective instrument in various uses, notably steganographic techniques. Generally, the confidential information is transformed into a bit stream, and then the image file is statistically modified to incorporate the binary information [7]. Aberrations can occur when the cover image is loaded with too much data, and the hidden content can become noticeable. As a result, the conventional approaches have a limited potential for concealing data.

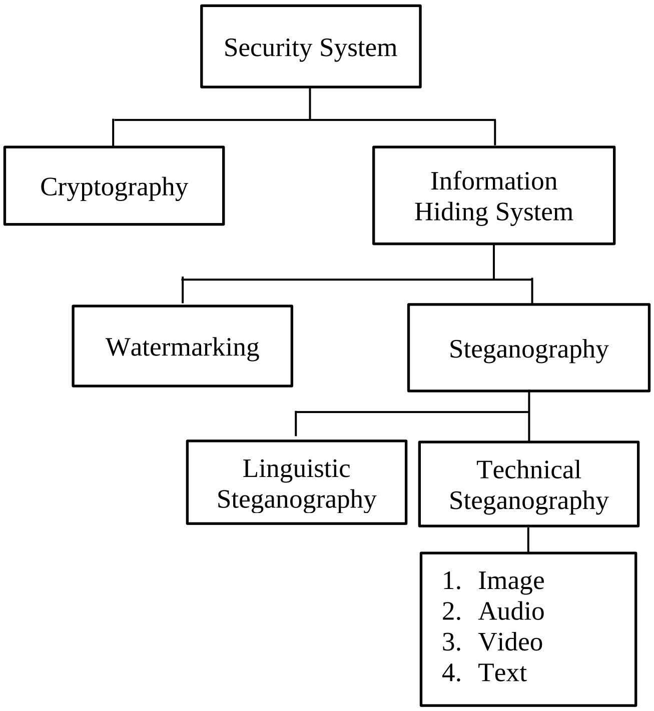

Fig. 1 Categorization of the security system

Three fundamental ideas are presented in contemporary steganography that is used for the construction of steganographic systems. These three concepts are:

1) Cover modification,
2) Cover selection,
3) Cover synthesis.

The cover image is the starting point for the procedure for a steganographer, which then adjusts the cover to mask information. On the other hand, the alteration can invariably result in integrating some new additions within the cover picture. The next concept of steganography is known as cover selecting encoding (CSE), and it is pretty close to feature extraction.

A steganographer chooses an organic, unaltered, and ordinary picture from an extensive collection of images capable of extracting information to use as a stego. Due to this approach's minimal yield, it cannot be utilized in real-life scenarios [8].

The third step involves the steganographer creating a stego picture with hidden messages. This paper proposes a simple yet robust image steganography technique that utilizes the convolution-based deep network to hide a secret picture with a cover picture. This suggested method performs better than the state-of-the-art techniques.

Section II of this study discusses related works in this field. The dataset utilized in this work and the preprocessing are presented in section III. Section IV presents the design and development of the model. In section V, we discussed the model performance and evaluation. Section VI concludes the article.

2. Literature Review

An earlier kind of image steganography involved adjusting the pixel's value by adhering to a predetermined mathematical approach or limiting the change brought about by encoding information [9-11]. Initially, conventional techniques, including LSB substitution, Discrete Wavelet Transformation, and Pixel Value Discretization, were utilized to conceal confidential data within a cover file by using the pixel of the cover picture [12].

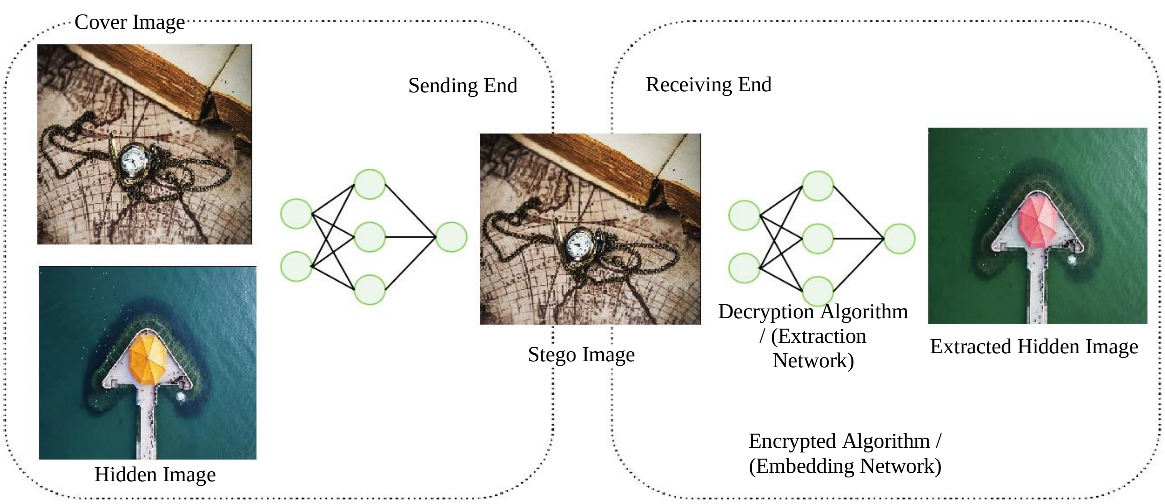

Fig. 2 Process flow diagram illustrating the method that is being presented. The pre-processing unit and the embedding networks are the components that make up the transmitting end. The combination layer is used in the procedure of the pre-processing module to combine the features that have been hauled out from both the cover picture and the hidden picture. The image quality may be reconstructed using the merged characteristics thanks to the encrypted network. At the receiver side, the final component is the extraction network, which is responsible for deciphering the stego picture to reveal the hidden picture

On the other hand, the traditional approaches have a limited potential for concealing information because of problems with their concealing capacities, which might result in the revelation of the existence of hidden material. Another learning methodology that sees widespread use in computer vision applications is known as deep learning.

In the arena of image steganography, deep learning techniques like modified machine learning algorithms and generative adversarial networks (GANs) [13], [14], [15] are among those that have been modified for use. These techniques' concealing capability, safety, and resilience have significantly improved compared to more conventional means. The reversible image steganography refers to a process in which steganography and the revealing of secret data are carried out simultaneously [16]. This method is more advanced if applied with deep learning.

In the F5 algorithm, the modifications have been evenly dispersed across the Discrete Cosine Transformation (DCT) factors to defend against statistical assaults [9]. In the first place, Wu *et al.* developed an embedded approach termed LSB+ correlation to roughly retain the residual dispersion of DCT coefficients. After that, the DCT coefficients are separated even more into four frequency bands so that the picture can be hidden. The high-frequency band has a low privacy preservation rate and higher encryption effectiveness.

In contrast, the mid-band, the DC band, and the low-frequency band all have increasing concealing rates, with the low-frequency band with the most significant concealing percentage. In various approaches, various distorting metrics are developed to quantify the deformation brought about as a result of data encapsulation [17] [18]. The syndrome trellis coding is a way to reduce this distorting as much as possible while still maintaining a level of security that is somewhat resistant to steganographic analytical techniques [19].

Patel et al. (2016) suggested that using cryptography with steganography will increase the general anti-detection quality [20, 21]. In Qiu et al. (2019) the authors make use of three distinct types of properties that are known as Local Binary Patterns (LBP), the average and the deviation of pixels to implement steganographic technology [22].

Conventional steganography suffers mainly from a lacklustre ability of concealment [23]. When trying to conceal sensitive data, tampering with an increasing amount of covering bits increases the risk that the data will be discovered. Because steganography relies on leveraging data patterns in the image pixels [24], steganalysis is a straightforward process of decoding [25, 26]. Due to this, the technique's safety is compromised.

The retrieved classified data may be of poor grade, which can weaken the system as a whole. It is also a problem that the secure transmission medium is almost exclusively text. In cases where a picture is required, only monochrome versions are employed. Using standard means to conceal the image pixels of a multiple-channel secret picture can be challenging within a second multi-channel cover picture. Nevertheless, this problem of concealing ability, which plagues the majority of existing techniques, can be addressed by employing deep learning-based methods. Because the models are so complicated, increasing capacity requires more storage, ram, and CPU time.

3. Data and Data Preprocessing

3.1. Dataset

This dataset is called the 'Flower Recognition' dataset, created as part of the 'DPhi Data Sprint #25: Flower Recognition'. The data comprises unprocessed JPEG pictures of five different kinds of blooms. This dataset comprises two segments: the 'train' dataset and the 'test' dataset. The 'train' is a directory that stores all of the photographs that will be utilized in the training process of the algorithm. There are five sub-folders labelled "daisy," "dandelion," "rose," and "sunflower," each of which contains photographs of a different kind of flower: tulip, sunflower, rose, and dandelion in this dataset. The 'test' dataset includes 924 different flower photos comprising flower names for these pictures, which are "daisy," "dandelion," "rose," "sunflower," and "tulip", respectively.

3.2. Data Preprocessing

Before parsing, the preprocessing unit extracts attributes from the covering and hidden pictures. Retrieving the most significant characteristics from high-resolution pictures helps ease the workload of the cover algorithm. The representing dimension of the input image should be in width * height * depth format. The input image to the system and the output image should be the same size. In the beginning, we used batch normalization on the input dataset. The 'prepare network' takes in the secret image and gives output as a (BATCH_SIZE, INPUT_HEIGHT, INPUT_WEIGHT, 150) tensor. Figure 3 presents the flow diagram of the preprocessing unit for this model.

After batch normalization, the preprocessing unit has three convolution branches. The first unit includes four layers of 3×3 convolution. After that, the next branch has four layers of 4×4 convolution. Four 5×5 convolution layers are included in the third convolution branch. All these procedures are done on both the cover and secret images separately. Following these steps, the secret and cover side outcome layers are concatenated in the concatenation layer, leading to the outcome of the 'concat_final' layer. Table 1 shows the parameters for Pre Processing.

Table 1. Parameters for preprocessing step

Parameter	Value
Filters	50
kernel size	4
padding	same
activation	tf.nn.relu

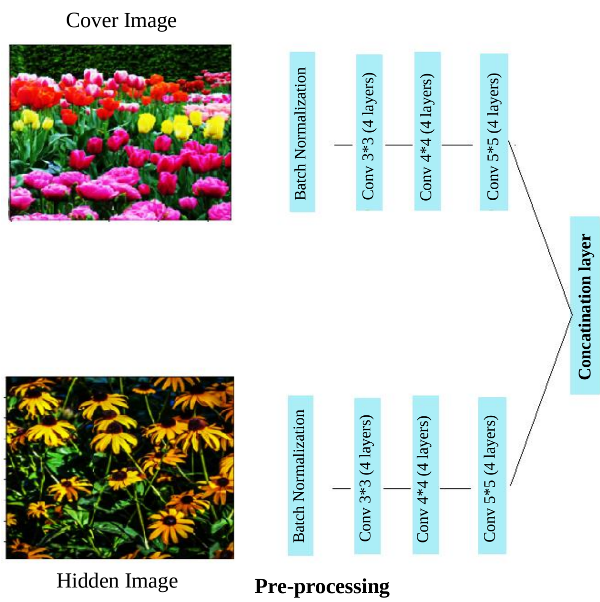

Fig. 3 The preprocessing flow diagram

The applications should be carefully considered before deciding the stride, filter size, or filter amount. The preprocessing unit's primary objective is to use convolutional stages of varying filter sizes and retrieve relevant and valuable characteristics that can be used in subsequent steps. The size of the filter used here is 50, which is a large number, so the system can start learning increasingly complex characteristics.

4. The Development of Model

This research presents a model with a three-part methodology. These components are the preprocessing module, the cover network, and the revealing network. The stego picture is reconstructed by an embedded net, and the preprocessing section prepares the system's cover picture and secret picture. The cover network aims to restore the steganographic picture that conceals a second, more sensitive picture within a more prominent version.

A carrier steganographic picture is used, and an extractor system finds the hidden image. The stego picture is created at the transmitting end, where the preprocessing unit and cover network are on the receiving side. The 'reveal network' is used to decipher the steganography and retrieve the original hidden picture.

4.1. The Cover Network

In order to generate a hidden region, the cover network uses the concatenation characteristics from the preprocessing step as the input. So, the cover network receives the results from the previous step and a picture for use as a covering. These two tensors are joined to form a new tensor with the values (BATCH SIZE, INPUT HEIGHT, INPUT WEIGHT,153).

After that, convolutions are executed, and a picture with these dimensions (BATCH SIZE, INPUT HEIGHT, INPUT WEIGHT, 3) is returned. In the convolution step of the 'hiding network', there are three branches, each containing four layers. The branches contain different dimensions of tensors. They are:

1) Branch 1: 3×3 convolution
2) Branch 1: 4×4 convolution
3) Branch 1: 5×5 convolution

After this, a concatenation layer is introduced, and Table 2 shows the parameters for Cover Network. At the end of the convolutional layers, the ReLU activating function is introduced to establish uniformity. This is done by assigning the maximum value as positive and the minimum as unfavourable.

The issue of vanishing gradients, frequent in designs with numerous layers, is circumvented using ReLU. This simplifies the learning process as more superficial and increases accuracy [27]. At the end of these procedures, the cover network gives the stego image as the outcome. The steps are described in Figure 4 below.

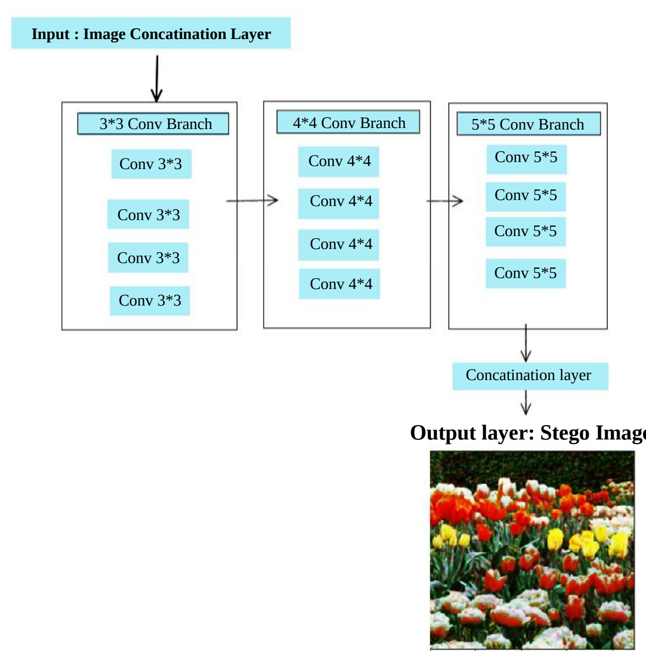

Fig. 4 Hide-net architecture as cover network

Table 2. Parameters for cover network

Parameter	Value
Filters	50
kernel size	4
Padding	Same
Activation	tf.nn.relu

Table 3. Parameters for noise layer

Parameter	Value
Shape	shape of tensor
Mean	0.0
Stddev	dev
Dtype	tf.float32

4.2. The Reveal Network

The picture produced by the Cover system is sent into the Reveal network, which then produces the revealed picture intended to have the same appearance as the secret image. Using a design similar to the cover network would appear to yield the most effective outcomes in retrieving the hidden picture with the least amount of data being lost.

The parameters employed in the 'reveal network' design are acquired through experimental study. The steps are described in Figure 5 below.

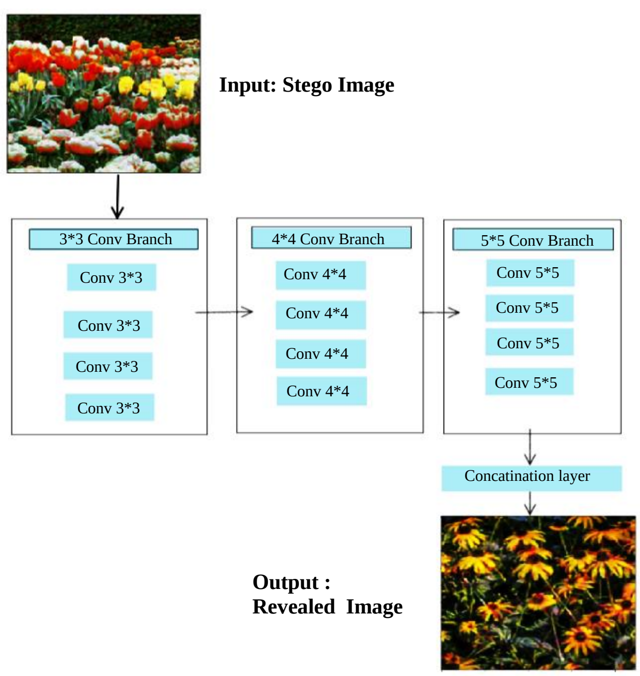

Fig. 5 Reveal network operation

The 'reveal network' system sends the stego image to the series of different dimensions of convolution layers and then produces the revealed image, which is expected to be the same as the hidden image.

4.3. The Noise Layer

When working on tasks linked to image processing, such as steganography, we must pay close attention to the images and ensure they all have the same amount of noise. A noise mask must be applied if the output pictures have a higher noise level than the inputs. This layer can add noise affecting all elements, resulting in a more unified production [28].

So, here we introduced a noise layer that provides outcomes in the form of values drawn randomly from normally distributed data. It is similar to the input tensor and has a mean value of '0.0' with 'std' as the standard deviation. It returns the tensor with the previously mentioned parameters. Table 3 indicates the parameters for the Noise Layer.

4.4. Tailored Loss Operation

There is a possibility that a standard loss function would not work for image steganography. Implementing a specialized loss operation can enhance the system's efficiency. This loss operation comprises four operations. They are beta, loss for the secret image, the cover image, and the final loss function, respectively. An entity similar to a tensor serves as the starting point for the beta function, which then generates a consistent tensor. The cover loss is determined by comparing the original covering picture to the final stego image generated by the covering network.

In contrast, the secret loss is determined by the 'reveal network' by comparing the secret input image to the retrieved secret image and calculating the difference between the two. In this case, the mean-squared error is the parameter used for calculating the difference. The combination of the losses incurred during cover and secret with beta function constitutes the total loss. A predictor's mean squared error (MSE) quantifies the mean of the squared values of the inaccuracies.

If the cover loss is signified as L_{cover} and secret loss are denoted as L_{secret}, then their mathematical representation is depicted in equations 1 and 2.

$$Lcover = |I - I'| \quad (1)$$

$$Lsecret = |S - S'| \quad (2)$$

Where 'I' depicts the original cover image and I' indicates the predicted cover image. Similarly, S indicates the original secret image, and S' depicts the secret image predicted by the system at the end of the procedure.

4.5. Tensor to an Image Operation

We introduced a tensor to the image function to transform the resultant tensor into an image. We employed the 'tf.convert_to_tensor' function to convert the input value to a tensor. The output of this operation is calculated utilizing 'tf.clip_by_value'.

Table 4. Comparision of PSNR values for different techniques

Paper	Technique used	PSNR Value
Rahim et al. [31]	Encoder-Decoder	29.600
Zhang et al. [13]	GAN	34.100
Subramaniam et al. [33]	Encoder-Decoder	34.550
Suggested Method in this study	CNN-based Deep Learning	65.678

This function clips the tensor values to a minimum and maximum as provided. The input tensor for the resulting function is computed using the sum of two different tensors. The maximum value for the resulting function is 1, and the minimum value is 0.

5. Results and Discussion

After calculating the capability of the developed framework, one or more picture steganography techniques with a potential comparable to that of the suggested model are evaluated. The results make it clear that the recommended design has a more concealing capability than state-of-the-art techniques, which may indicate that every bit of the secret picture is concealed within every bit of the cover picture.

We utilized Adam optimizer to optimize the model. Adam is a substitute optimization method for stochastic gradient descent for developing deep-learning systems [29]. Adam, or the Adaptive Momentum Estimation, is a technique that involves computations on appropriate learning speeds for every variable of the models.

The peak signal-to-noise ratio, often known as PSNR, is the ratio that describes the relationship between the most significant achievable power of a picture and the power of any interference that degrades the clarity of its depiction. In order to calculate the PSNR of an image, it is essential to contrast the target image with a perfect example of a good image with the most conceivable power. The MSE and PSNR readings of the suggested approach are provided and evaluated to the results of techniques considered to be state-of-the-art [30]. They are utilized to contrast the grade of image compression. The clarity of the image content and the image quality, after it has been restored, improves in direct proportion to the PSNR. So, a higher PSNR value indicates a more efficient model. In our study, the proposed model reached a PSNR value of 65.677. This is far higher than the other contemporary image steganography techniques. The comparison of PSNR values for different techniques is shown in Table 4.

We used the universal image quality index, or UQI [34], to assess the various picture quality evaluation metrics. When we talk about quality evaluation methods being "universal," we imply that they are not dependent on the pictures being evaluated, the viewing settings, or the specific individuals doing the evaluation. The dynamic range of the UQI is between -1 and 1. The UQI value for this experimental study reached a value of 0.878. We also utilized spatial correlation(SCC) co-efficient for the quality assessment of the resulting images [35]. When the outputs of the original cover and the hidden images were compared using SCC, the value was 0.809. Table 5 presents the different evaluation metrics parameters of the model and their values computed for this study.

Table 5. Parameters for evaluation of proposed model

Parameters	Values
PSNR	65.678
UQI	0.878
SCC	0.809

Compared to the other ways, the PSNR values for the suggested technique are higher than those of the other techniques. The Color image is employed as the covert medium, contributing to the fact that the suggested approach has tremendous potential for concealing data.

The presented findings make it amply evident that the suggested framework possesses superior protection, resilience, and perceptual quality with the ability to conceal image data.

6. Conclusion

This research suggests a compact yet straightforward design to accomplish the steps from beginning to end of image steganography. The convolutional neural networks served as a source of inspiration for the presented framework. The preprocessing unit, the cover network, and the revealing network are the three components that make up the overall structure. For the cover network to successfully conceal the hidden picture within the cover picture, the pretreatment unit must first prepare the input pictures. The stego image formed by the cover network is passed via the revealing network, where the hidden data is retrieved. The suggested method's better PSNR value demonstrates that it is more secure and robust than previous image steganographic techniques, including standard and deep learning approaches. The other performance metrics used in the proposed method are UQI and SCC focus more on obtaining a quality image. The proposed method is superior in transparency and can make stego pictures highly comparable to the cover picture provided as input.

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